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[www.elsevier.com/locate/procedia](http://www.elsevier.com/locate/procedia)**International Symposium of Transport Simulation 2014****Latent Class Analysis for Driving Behavior on Merging Section****Masami Yanagihara <sup>a,\*</sup>, Nobuhiro Uno <sup>b</sup>, Toshiyuki Nakamura <sup>c</sup>**<sup>a</sup> *Department of Civil Engineering, Tokyo Institute of Technology, 2-12-1-M1-20,  
O-okayama, Meguro, Tokyo 152-8552, Japan*<sup>b</sup> *Graduate School of Management Kyoto University Katsura Nishikyo-ku, Kyoto, 615-8540 Japan*<sup>c</sup> *Department of Urban Management Kyoto University Katsura Nishikyo-ku, Kyoto, 615-8540 Japan*

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**Abstract**

This study proposes a modeling framework, and the complicated phenomena in merging sections are analysed with the model. The proposed modeling framework is based on the latent class model, and contains a simplified estimation method for all parameters. In the model, it is assumed that driving behaviors consist of multiple driving-modes, and the latent driving-modes are based on drivers' intentions or surrounding circumstances. The modeling structure enables us to analysing complicated phenomena in merging sections which often becomes a bottleneck or an accident hotspot because of drivers' inevitable lane-changing and vehicles' complicated movements. Driving behaviors of vehicles on main-lane of a merging section are analysed and effects of information for safety driving are verified.

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*Keywords:* driving behavior, car following, latent class model

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**1. Introduction**

Car driving behavior is a complicated task in general. It requires drivers to recognize the surrounding circumstances and, at the meantime, to operate steering wheels, accelerator pedal and brake pedal. On fairly straight sections of expressway, the driving behavior is rather simple, where driver would basically pay attentions to vehicles in front. Conversely, in merging sections, one would probably observe a much more complicated driving behavior. Almost all drivers in merging sections should pay attention to

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\* Corresponding name: Masami Yanagihara. Tel.: +81-3-5734-2575  
E-mail address: [yanagihara@plan.cv.titech.ac.jp](mailto:yanagihara@plan.cv.titech.ac.jp)

vehicles on other lane and operate their vehicles run safely even when their vehicles exist in the main-lane. As a consequence, a merging section often becomes bottleneck or accident hotspot, as long as drivers should pay fully attention to movements of surrounding vehicles and making their decisions in a very short time frame, failure may easily occur. Analysis for the complicated driving behavior on merging section is required in order to make the cause of traffic congestion and accidents clearer.

Modeling drivers' behaviors in merging sections is important task for understanding the complicated phenomena from the point of view of traffic congestion and accidents. Whole vehicle maneuvers should be consist of several behaviors as simple car-following, free driving, driving while wary of merging car, emergency stopping, and so on. Most studies mainly focus on general relationships between surrounding circumstances and vehicle maneuvers, which are divided into several modules of driving behaviors. And these modules are separately analysed and modeled. As is often the case with analytical process of traffic flow, these modules separately built are jointly utilized for simulating traffic condition. In order to understand and simulate a driver's behavior at merging section precisely through the process of modeling and reproduce the traffic flow accurately by the simulation, it is necessary for us to apply a common modeling framework that can cover the various driving behavior under the different circumstances.

A traffic micro simulation with accurate models about drivers' behaviors is a possible tool for analysing complicated phenomena with danger situations. Bonsall et al. (2005) made a traffic simulation model for assessment of traffic safety in complicated situations. The model consists of rules of speeds in free-flowing traffic, headways between vehicles, acceleration profiles, and so on. The result of simulation indicates that the safety-related movements are caused from the use of inappropriate parameter values. On the other hand, Xin et al. (2008) produced a model with reaction time depending on individual driver characteristics and instantaneous traffic conditions. The model has a capability to replicate both normal and unsafe driving behavior that could lead to vehicle collisions. The produced model was validated with real crash trajectories. These results indicate that it is necessary for us to consider situation-specific behavior in order safety assessment with simulation models.

Among many researches on driving behavior that aim to enhance simulation accuracy, Koutsopoulos et al. (2012) proposed a car-following model based on latent class model (LCM) which deals with the differences between several (latent) states, such as deceleration, acceleration, and do-nothing. This structure makes it possible to integrate multiple acceleration controlling behaviors into one modeling framework. On the other hand, Chevallier et al. (2009) produced a modeling solution that correctly reproduces merging with new car-following rules and a new insertion decision algorithm. It is indicated that merging behavior should be reproduced by some special structures such as the particular algorithm proposed by Chevallier et al.

The objective of this paper is to propose a driving behavior model which enables us to analyse car-following behaviors on merging sections considering the latent driving-modes. Furthermore, all parameters were estimated using vehicle trajectory data extracted from driving experiments with a driving simulator as a case study for a trial of applying the framework. In the experiment, vehicles of the subjects run on a main-line of an expressway with a merging section, and 2 types of merging-support-information is provided to the subjects in order to analyse the effect of the information in terms of enhancement in safety.

## **2. Framework of the model**

### *2.1. Model design*

The proposed model integrates multiple car-following behaviors considering the latent variables representing driving intentions. The model is described based on latent class model (LCM) structure, and

contains multiple driving-modes, corresponding with intentions of drivers for maneuvering vehicles, as latent classes. It is expected that the proposed model provides us with a unified framework which can analyse and reproduce various driving behaviors even in merging sections. Focusing on a car-following behavior of a driver, there is a high possibility that the driver might change the way to drive and follow the leading vehicle according to the traffic and road condition. For example, it is natural that the driver might give a more sensitive response to the movement of leading vehicle under busy traffic condition at the merging section than under less busy condition at straight section, even if the relative velocity and time-headway to the leading vehicle themselves are assumed to be the same. It is assumed that the change in driving and car-following might be derived by the change in 'driving-mode'. These driving-modes are assumed to be temporally changing according to the surrounding circumstances of the driver. The factors representing the surrounding circumstances are assumed to consist of the relative distance / velocity to leading / neighbouring vehicles which are able to be seen from the driver.

## 2.2. Outline of the framework

A detailed modeling framework based on the discussion above is shown in Fig. 1. The proposed framework in Fig. 1 is assumed to consist of three driving-modes for the case study in this paper. The number of the driving-modes treated in the framework can be flexibly defined considering the driving behavior focused on the corresponding data. This model structure contains unobservable changes of the driving-modes in time series and observable variables with input / output values related to these driving-modes, and the proposed framework hypothesizes a latent decision making process for those driving-modes. The variable  $l_{n,t}$  indicates an unobservable driving-mode of individual  $n$  at time  $t$ , and  $x_{n,t}$  /  $a_{n,t}$  is input / output values of this model. In the case of Fig. 1, the variable  $l_{n,t}$  is to be a driving-mode A, B or C, and four transitions of driving-modes are assumed: A to B, A to C, B to A and C to A. Three car-following models corresponding with three driving-modes are defined according to the modeling framework in Fig. 1. In this case, we expect the three driving-modes to be estimated into *following*, *free-driving* and *emergency-deceleration for merging*.

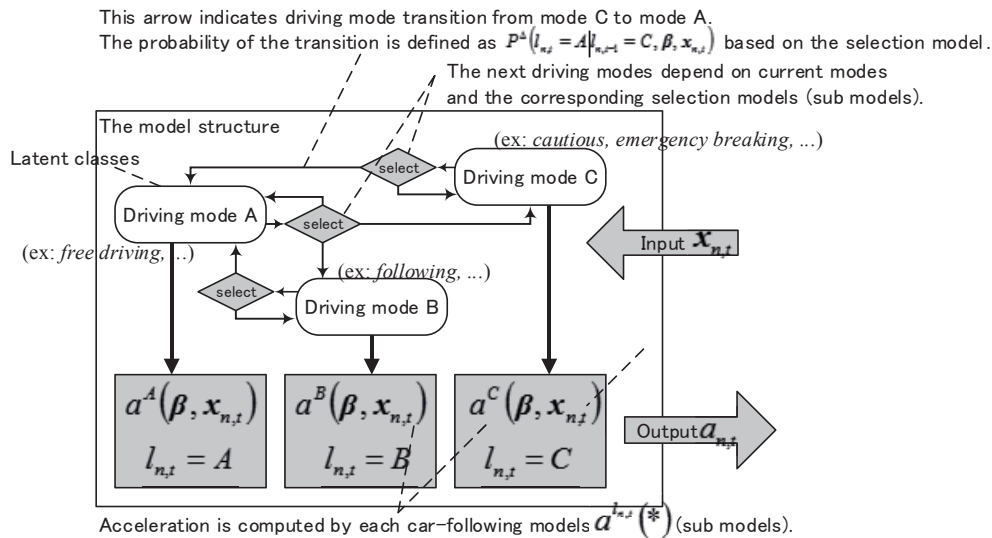


Fig. 1: A modeling framework for the case study of this paper.

The structure of transition between driving-modes enables us to capture and analyze state dependency in decisions of driving behavior. In this study, it is assumed that the temporal changes of the driving-modes indicate transition of drivers' intentions for manoeuvring vehicles. In addition, a driving-mode at current time step is assumed to be stochastically determined according to the previous driving-mode and surrounding circumstances, and it is described by a multinomial logit type model.

### 2.3. Model formulation

The probability of the transition among driving-modes is defined by Eq. (1). The utility among the driving-modes and each time steps are defined and a probability of a transition is assumed to be expressed as a multinomial logit model. According to the current driving-mode, current acceleration value  $a_{n,t}$  is calculated from Eq. (2) and Eq. (3), which is assumed to be a liner model for acceleration. The explanatory variables in transition and acceleration models mainly consist of relative distance and velocity between subject vehicle and leading / merging vehicles.

$$P^{\Delta}(l_{n,t} | l_{n,t-1}, \boldsymbol{\beta}, \mathbf{x}_{n,t}) = \frac{\exp(u^{l_{n,t}, l_{n,t-1}}(\boldsymbol{\beta}, \mathbf{x}_{n,t}))}{\sum_{k_{n,t}} \exp(u^{k_{n,t}, l_{n,t-1}}(\boldsymbol{\beta}, \mathbf{x}_{n,t}))} \quad \text{eq.(1)}$$

$$a_{n,t} = a^{l_{n,t}}(\boldsymbol{\beta}, \mathbf{x}_{n,t}(\boldsymbol{\tau})) := \boldsymbol{\beta} D^{l_{n,t}} \mathbf{x}_{n,t}(\boldsymbol{\tau}) \quad \text{eq.(2)}$$

$$\{D^{l_{n,t}}\}_{i,j} = \begin{cases} 1 & \text{if we use parameter } \{\boldsymbol{\eta}\}_i \text{ with } \{\mathbf{x}\}_j \text{ in } a^{l_{n,t}}(\boldsymbol{\eta}, \mathbf{x}) \\ 0 & \text{otherwise} \end{cases} \quad \text{eq.(3)}$$

Where

- $P^{\Delta}(l_{n,t} | l_{n,t-1}, *)$  : Probability of changing to or keeping  $l_{n,t}$  while selecting  $l_{n,t-1}$
- $\boldsymbol{\beta}, \boldsymbol{\tau}$  : Parameters to be estimated
- $l_{n,t}$  : Latent driving-mode
- $n$  : Index of consecutive trajectories (vehicles)
- $t$  : Index of observed time step
- $\mathbf{x}_{n,t}(\boldsymbol{\tau})$  : Surrounding situation value of vehicle  $n$  at time  $t$ , with late time  $\boldsymbol{\tau}$ .
- $a^{l_{n,t}}(\boldsymbol{\beta}, \mathbf{x}_{n,t}(\boldsymbol{\tau}))$  : Computed acceleration value at time  $t$  while selecting  $l_{n,t}$

All parameters are estimated by maximizing the value of a log likelihood function represented by Eq. (4), which is expressed by the acceleration residual values. From the viewpoint of convergence in the estimation process, it is terrible to maximize general log-likelihood functions of LCMs in terms of time necessary for convergence. For this reason, in this study, the log likelihood function has been simplified for efficient convergence. In this simplified log likelihood function, it is assumed that acceleration values of each time step for each driving-mode are outputted within a time period in proportion to the probability of the driving-mode. In this assumption, each time step is divided into the several parts (time periods), and the number of divided part is equal to the number of driving-modes. The maximizing problem is equivalent to a problem that integrates some of weighted multiple regression models estimating liner

parameters  $\beta'$  as shown in the right-hand side of eq. (7), and the estimation process guarantees the convergence of the parameters  $\beta'$ . Due to this method, the estimation result contains additional information about those regression models such as the fitness of the regression models.

$$LL(\beta, \tau | X) = \sum_n \sum_{t=1}^T \sum_{l_{n,t}} P(l_{n,t} | \beta, X) (a_{n,t}^* - a^{l_{n,t}}(\beta, x_{n,t}(\tau)))^2 \quad \text{eq. (4)}$$

$$P(l_{n,t} | \beta, X) = P^\Delta(l_{n,t} | l_{n,t-1}, \beta, x_t(\tau)) \times P(l_{n,t-1} | \beta, X) \quad \text{eq. (5)}$$

$$P(l_{n,1} | \beta, x_{n,1}(\tau)) = 1 / \text{number } l \quad \text{eq. (6)}$$

$$\max_{\beta} LL(\beta, \tau | X) \equiv \max_{\beta', \tau} \left( - \min_{\beta'} \left( \sum_n \sum_{t=1}^T \sum_{l_{n,t}} P(l_{n,t} | \beta', X) (a_{n,t}^* - a^{l_{n,t}}(\beta', x_{n,t}(\tau)))^2 \right) \right) \quad \text{eq. (7)}$$

Where

$X$	: All observed data
$LL(\beta, \tau   X)$	: Log likelihood value for a consecutive trajectory
$P(l_{n,t}   *)$	: Probability of selecting $l_{n,t}$
$a_{n,t}^*$	: Observed acceleration value at time $t$

### 3. Case study

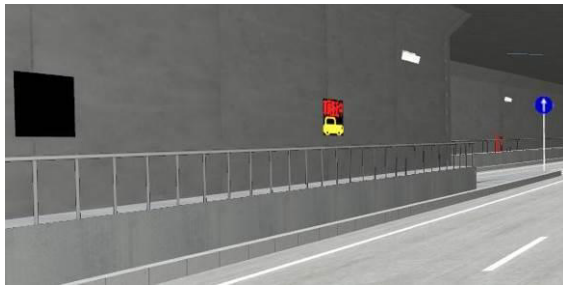
#### 3.1. Data collection

The parameters of the proposed model were estimated using a trajectory data set obtained from the experiment using driving simulator (DS) as a case study. We did driving experiments for 57 subjects, and collect the data on vehicular manoeuvring and driving behavior. Table 1 shows the number of the subjects classified by their age. Although there is diversity in the number of subjects against the age, the elderly subjects are also included and the 57 subjects are not small number compared with the similar experiment.

The vehicular trajectory is observed in experiments on a virtual tunnel section of urban expressway which contains a merging area. In the DS experiment, the subject's vehicle runs along the main line of the expressway. We set the scenarios where the other vehicle merges into the main line when the vehicle of the subject is approaching to the merging point. Just before reaching the merging section, the information that notifies the drivers travelling on main line of the approaching merging vehicle was provided to the subjects. The information was provided by two types of devices shown in Fig. 2. The devices in the left and right hand sides are called Vehicle-Tracking-Information-Board (VTIB) and the Conventional-Character-Information-Board (CCIB). Both information boards flash when a merging vehicle passes a certain point on the merging lane to notify the drivers of its approaching. CCIB is a simple system with a single blinking information showing "approaching merging vehicle" in Japanese. On the other hand, VTIB informs the rough position of the merging vehicle with five continuous LED board with a flashing pictogram of car in parallel with the movement of the merging vehicle. All the subjects were required to drive the road twice with the information provided by VTIB and CCIB for the data collection.

Table 1: The number of the subjects of the experiment

age	the number of subjects
20-29	19
30-39	5
40-49	12
50-59	1
60-69	14
70-75	6
Total	57



VTIB



CCIB

Fig. 2: Two types of information boards.

The merge nose with the information board was assumed to be located around 300 meters before the end point of road section for experiment. Fig. 3 shows the road alignment used for the experiments. This road consists of a downward slope, an ogee and the merging section targeted. CCIB is installed at 1760m point of the road in Fig. 3, and a series of 5 VTIBs are installed in every twenty meters between 1680m and 1760m.

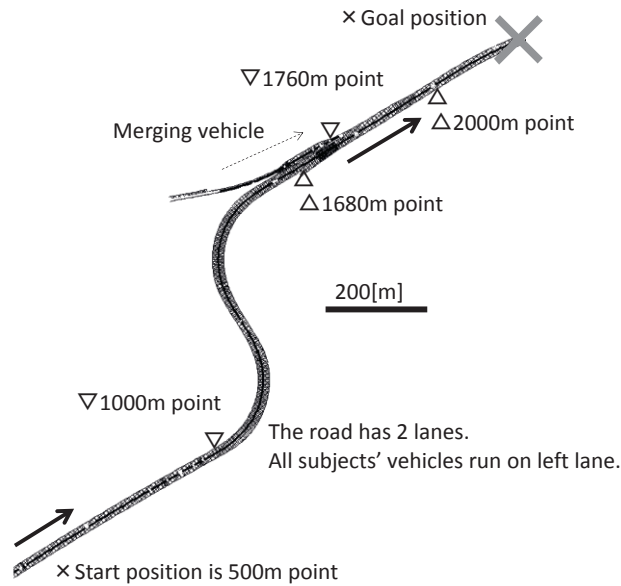


Fig. 3: The using section of the road for the experiments.

The trajectory data for the model estimation was extracted from the logging data of the DS in every 0.2 seconds. Since this study is aimed at analyzing the car-following behavior at the road section including merging, it is necessary for us to define the vehicular condition that can be regarded as a car-following. In this study, it is assumed that a vehicle traveling within 90 meters from the vehicle in front is regarded as the one which consciously follows its leading vehicle, and the corresponding data on driving behavior and vehicular manoeuvring are extracted.

### 3.2. Parameters estimation process

In order to analyze the effects of VTIB and CCIB, two explanatory variables about each information-board (VTIB is visible / CCIB is visible) are included especially in the function related to the selection of a particular driving-mode (driving-mode C in Fig. 1).

All parameters of proposed model in the case study are estimated by maximizing the likelihood function denoted by Eq. (4) with a heuristic method. The heuristic method is an integrated method composed of simulated annealing (SA) and down-hill simplex method (DSM). In the integrated method, liner parameters for acceleration  $\beta'$  are converged with multiple regressions, and parameters indicating reaction times  $\tau$  for acceleration are calculated and converged by golden section method with limited span between 0 second and 5 seconds. The calculation process is shown in the flow chart (Fig. 4). In the process to calculate a log likelihood value, parameters for acceleration  $\beta'$  and reaction time  $\tau$  are calculated so as to maximize the likelihood value with the other temporarily fixed parameters. This process is shown on the right side of Fig. 4. The other parameters  $\beta''$ , which are ones for defining the probabilities of driving-modes selection models, are estimated through a search process of SA and DSM as shown on the left side of Fig. 4.

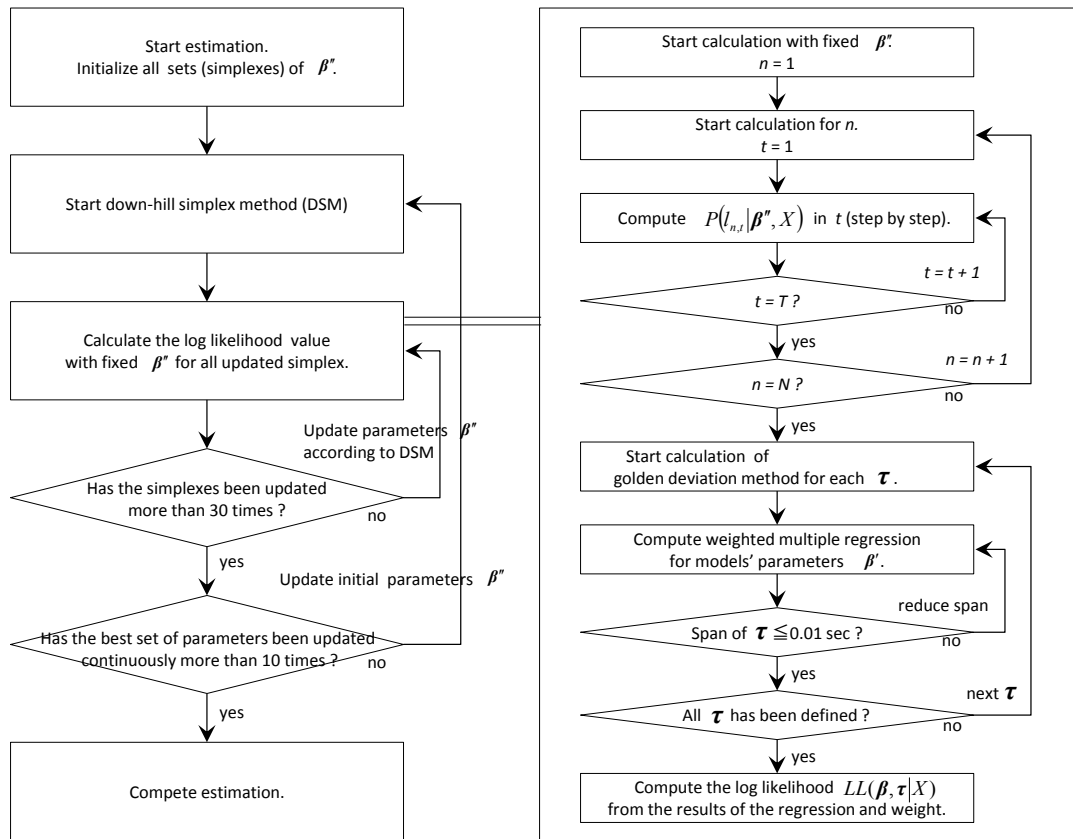


Fig. 4: The calculation flow of the parameter estimation.

### 3.3. Parameters estimation result

Table 2 shows the important information including log likelihood value, RMSE (Root Mean Square Error) and AIC (Akaike Information Criteria) of the estimated model. This table also shows the one of the conventional multiple regression model of acceleration. While the similar result has been shown in the past studies, the acceleration error of the proposed driving behavior model might be smaller than that of the conventional one according to RMSE in the table. Furthermore, the value of AIC suggests that the proposed model with latent classes might be a better model compared with the conventional one. So as to clearly analyze the effect of information provision at merging section by the simple structure of model in the case study, the explanatory variables and the assumed latent classes are relatively limited, and hereby the likelihood ratio of the proposed model is 0.21 and might remain relatively low. Accordingly there is a possibility that the proposed model might be improved in terms of its fitness to the observed driving behavior including acceleration and deceleration of vehicle.



Table 2: The likelihood value of the estimated model

Model	Log likelihood	Likelihood ratio	RMSE [m/s <sup>2</sup> ]	Parameters	AIC
Latent class model (provided model)	-3362.9	0.21	0.119	44	6637.7
A multiple regression model	-3650.0	0.14	0.129	8	7284.0
Average value of acceleration	-4248.6 = -fluctuation		(0.151) = Std.	(1)	(8495.3)
				Sample	28214

We define three types of driving-modes for the model framework of this case study. Based on the results of the estimation, those were named “*cautious*”, “*others*” and “*following*”. Table 3 shows the results of weighted multiple regression models of accelerations of each driving-mode. The weight values in Table 3 are obtained by the summation of probabilities of selecting each driving-mode  $l_{n,t}$ . This weight is regarded to indicate the expected number of plots of each driving-mode observed in the data of the case study. This result indicates that the driving-mode “*others*” is expected to occupy the most part of the driving in the experiment. However the adjusted  $R^2$  suggests that the goodness of fit of the model for “*others*” is lower than that of “*cautious*” and “*following*”. Considering explicitly driving-modes, the goodness of fit of acceleration model tends to be improved. There is a possibility that driving-mode “*others*” might still contains several different driving-modes and further classification of “*others*” into several driving-modes might contribute to improve the goodness of fit of acceleration model.

Table 3: The results of the weighted multiple regression analyses (About the good ness of fit)

Driving-mode $l_{n,t}$	$R^2$ Adj	Weight $\sum_{l_{n,t}} P(l_{n,t}   \beta, *)$	reaction time [s]	Average	
				acceleration [m/s <sup>2</sup> ]	distance to front vehicle[m]
<i>following</i> (B)	0.265	5759.1	2.3	-0.1±0.5	40.2±13.0
<i>others</i> (A)	0.191	21801.0	3.9	0.0±0.4	63.4±12.4
<i>cautious</i> (C)	0.311	653.9	0.0	-0.5±0.7	66.5±15.5

It is assumed that each driving-mode has its own reaction time as an important parameter of driving behavior model with latent classes. As shown in Table 3, the reaction time estimated for “*following*” is 2.3 seconds and relatively short compared with the one for “*others*”. In addition, the distance to the vehicle in front of “*following*” tends to be shorter than that of other modes. According to the estimated result of linear type of car-following model, the “*following*” mode is regarded to represent the intentional car-following behavior to the vehicle in front. Concerning “*cautious*” mode, the estimated reaction time becomes extremely small, and it suggests that the drivers might react the change in behavior of surrounding vehicles in a very sensitive manner.

Table 4 also shows the result of the parameters of weighted multiple regression models of acceleration. All of the models are assumed to have the same set of explanatory variables, namely speed of the subject driver’s vehicle, relative speed / distance to leading / merging vehicle and dummy variable representing the existence of the merging vehicle. The dummy variable is 1 if the merging vehicle exists; otherwise 0.

Table 4: The results of the weighted multiple regression analyses (About the parameters)

driving-modes explanatory variables	<i>following</i> (B)			<i>others</i> (A)			<i>cautious</i> (C)		
	t-value			t-value			t-value		
speed of the subject's vehicle	-9.1E-03	-6.2	***	-5.2E-02	-49.7	***	-5.0E-02	-8.5	***
relative speed to leading vehicle	1.6E-01	75.9	***	6.5E-02	48.3	***	9.8E-02	15.6	***
relative distance to leading vehicle	-3.3E-04	-3.8	***	-6.4E-04	-7.0	***	5.3E-03	18.8	***
relative speed to merging vehicle	1.2E-03	8.6	***	2.0E-03	2.1	**	1.8E-03	24.1	***
relative distance to merging vehicle	-3.6E-02	-18.2	***	-8.3E-03	-1.3	*	-3.0E-01	-57.8	***
existence of merging vehicle	-1.3E-01	-12.5	***	-4.4E-02	-1.4	*	7.0E-01	42.6	***
const.	2.1E-01	7.1	***	9.0E-01	24.5	***	-2.6E-01	-2.5	***

(\* P&lt;10%, \*\* P&lt;5%, \*\*\* P&lt;1%)

The driving-mode named “*cautious*” has bigger absolute values of parameters of variables related to merging vehicle. It shows that drivers tend to pay more attention to the merging vehicle while “*cautious*” mode is selected by the drivers. On the other hand, the absolute values of corresponding parameters of “*others*” are relatively small ones, and then the mode named “*others*” contains less 1 or 5% significant variables related to the behaviors of the merging vehicle. The result suggests that the drivers in the “*others*” tend to pay less attention to the merging vehicle. In the case of mode named “*following*”, the parameter of the relative speed to the leading vehicle is relatively large, and it seems that the characteristics of acceleration model might be consistent with its name of “*following*”.

According to the modeling framework in Fig. 1, the model describing the transition probability among the modes is assumed to be composed of a multiple logit model and two different binary logit models. The multiple logit model, which has three choices is used when the mode named “*following*” is selected. The three choices of the model are keeping the mode named “*others*”, changeing driving-mode from “*others*” (A) to “*following*” (B) and changeing driving-mode from “*others*” (A) to “*cautious*” (C). Utility functions are defined for the three choices, and the function for keeping the mode named “*others*” is defined 0. On the other hand, the two different binary logit model, namely the model from driving-mode “*following*” (B) to “*others*” (A) and the one from driving-mode “*cautious*” (C) to “*others*” (A) are represents the probability that the driving-mode changes from “*others*” / “*cautious*” to “*following*” or not.

Table 5 shows the estimated parameters of the model describing the transition probability among the modes. Four sets of estimated parameters are shown in Table 5 according to the four different utility functions explained above. It is assumed that all of utility functions have the common set of explanatory variables, namely relative distance values to leading / merging vehicle and dummy variable representing the existence of the merging vehicle. Especially in the utility functions of transition between “*cautious*” and “*others*”, dummy variables representing the visibility of information-boards are defined. The dummy values are defined as 1 if the flushing information-boards (VTIB or CCIB) are visible from the subject drivers; otherwise 0. We try to analyze the effect of the information-boards according to the estimated parameters for these dummy values.

Table 5: The estimated parameters in driving-modes selection models

explanatory variables	Parameter value	STD	t-value
from driving-mode <i>others</i> (A) to <i>following</i> (B) :			
const.	9.4	1.7E-01	56.37 ***
relative distance to leading vehicle	-0.4	6.4E-03	-56.89 ***
relative distance to merging vehicle	-29.3	5.3E+01	-0.55
existence of merging vehicle	4.2	7.5E-02	56.43 ***
from driving-mode <i>following</i> (B) to <i>others</i> (A) :			
const.	-10.8	1.9E-01	-56.28 ***
relative distance to leading vehicle	0.4	7.0E-03	56.10 ***
relative distance to merging vehicle	14.8	2.3E+01	0.64
existence of merging vehicle	-8.4	1.5E-01	-56.26 ***
from driving-mode <i>others</i> (A) to <i>cautious</i> (C) :			
const.	-16.6	6.0E+00	-2.76 ***
relative distance to leading vehicle	-4.1	6.1E-02	-67.61 ***
relative distance to merging vehicle	2.5	3.6E-02	67.55 ***
existence of merging vehicle	-12.5	$+\infty$	0.00
VTIB is visible	-3.9	$+\infty$	0.00
CCIB is visible	-10.1	$+\infty$	0.00
from driving-mode <i>cautious</i> (C) to <i>others</i> (A) :			
const.	-6.3	1.1E-01	-56.68 ***
relative distance to leading vehicle	0.8	1.4E-02	56.78 ***
relative distance to merging vehicle	-32.9	8.9E+01	-0.37
existence of merging vehicle	-10.8	1.9E-01	-56.72 ***
VTIB is visible	2.7	$+\infty$	0.00
CCIB is visible	-37.5	7.7E+04	0.00

(\* P&lt;10%, \*\* P&lt;5%, \*\*\* P&lt;1%)

The parameters for the relative distance to the leading vehicle are positive in the utility functions of transitions to “*others*”, but on the other hand the corresponding parameters are negative in the utility functions of transitions from “*others*”. In other words, the estimated parameters suggest that the drivers tend to take the modes “*following*” and “*cautious*” rather than “*others*” when the relative distance to the leading vehicle becomes small.

The parameters of existence of merging vehicle are statistically significant except for the model describing transition from driving-mode “*others*” (A) to “*cautious*” (C). On the other hand, the parameter of relative distance to merging-vehicle, which represents not only the distance but the existence of the merging-vehicle, is statistically significant for the model describing transition from driving-mode “*others*” (A) to “*cautious*” (C) instead. Especially, the corresponding parameters are negative in the utility functions of transitions to “*others*”. This result suggests that the drivers encountering the merging vehicle do not tend to change their driving-mode to “*others*” and distance to the merging vehicle is considered only when the driver changes his / her driving-mode to “*cautious*”.

While we aim to analyze the effect of information on oncoming merging vehicle provided upon the change in driving-modes, the parameters for the information-boards are statistically insignificant at this moment in time. It is because the transition of driving-modes might be strongly affected by the existence of merging vehicle and the distance to the leading vehicle. It is necessary for us to elaborate the definition of explanatory variables and estimate the parameters again. However if we can found a significant deference of the absolute value size of parameters between VTIB and CCIB, we could analyze the effect of the information according to the drivers' latent intension using the provided modeling framework. In this case, an absolute value of a parameter for an information-board is a little larger than the others, and this result might indicate the tendency to keep the driving-mode “cautious” while the CCIB.

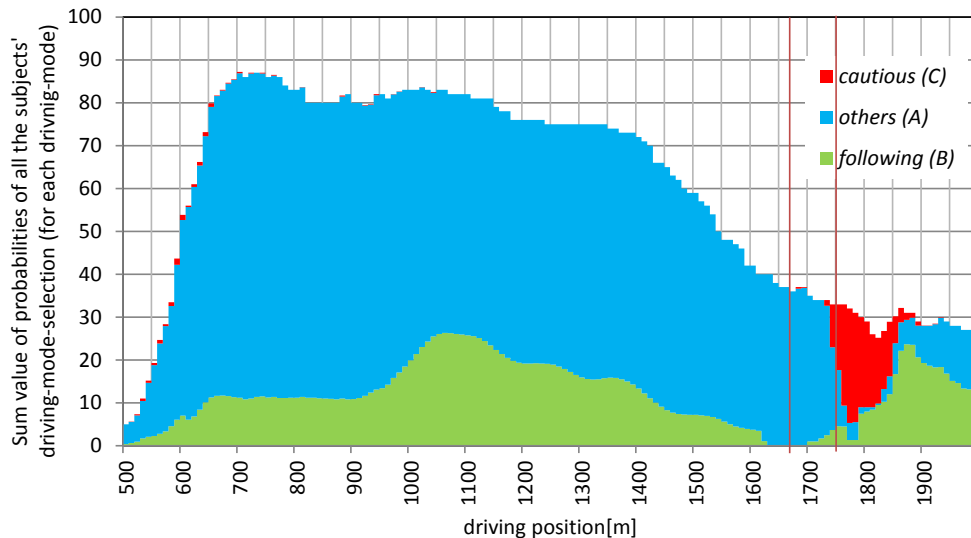


Fig. 5: Estimated driving-mode against longitudinal position along road.

Fig. 5 shows the estimated driving-mode based on the model describing the transition probability against the longitudinal position along the road utilized for experiment. The section between two red lines in Fig. 5 corresponds with the one where the information-boards are visible for the driver, and there is a merging section immediately after that section. The vertical axis represents the summation of mean probability of each driving-mode for all the valid respondents at every ten meters. The value of vertical axis shows the relative distribution of each driving-mode against the longitudinal position along the road. Due to the way to extract the valid vehicular data explained in section 3.1, the number of valid respondents is not constant along the road.

According to the estimated driving-mode, the mode named “cautious” is found especially after the section where the information-boards are visible. The driving-mode named “following” is mainly found in an area between the section from 1000[m] to 1400[m] where the leading vehicle slows down its speed because of the ogee and the subject easily follows the leading vehicle.

Considering the fact that the large proportion of “cautious” is found around the merging section, there is a possibility that the proposed model with the latent class variables might contribute to giving us a rough estimation of driving-mode from the vehicular trajectory data. The estimated driving-modes will be noticeable and meaningful indices for assessments of drivers' behaviors.

#### 4. Conclusion

A modeling framework for drivers' behaviors is provided in this paper. The provided modeling framework represents transitions of (latent) driving-modes. The framework also provides the fast-converging method of the estimation for the model parameters with simplified likelihood.

For the case study, all the parameters of the provided model with three driving-modes are estimated targeting to the drivers' behaviors on a merging area. The result of the estimation of the case study indicates that the provided model might be a better model compared with the conventional one. Furthermore the result shows the future of the behaviors of the drivers with each estimated driving-mode and the relation between these driving-modes and surrounding circumstances. Especially, the drivers' cautious behavior at merging section was divided from other driving-modes.

In this modeling framework it is assumed that a driving-mode indicate a latent intension for the driving of the driver. Therefore drivers' latent intension can be taken only from movements of vehicles using this framework. There is some possibility to analyse the driving safety from a psychological viewpoint with the extracted intension in the future.

For the sake of simplicity, we install a few parameters and driving-modes in the model of the case study. However, the likelihood ratio of the estimated proposed model might remain relatively. Accordingly there is a possibility that the proposed model might be improved in terms of its fitness to the observed driving behavior with additional kinds of parameters and driving-modes. In this case study, the effect of information-boards to driving-modes is insignificant, but there is possibility to find significant effect in the improved models.

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